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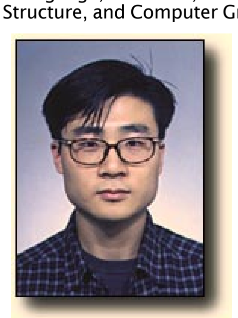

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Introduction

Surface finish is a key machining process integral to evaluating the quality of a particular product. Many different attributes of the product, including surface friction, wearing, heat transmission, the ability to distribute and hold a lubricant, the ability to accept a coating, and the ability to resist fatigue, are at least partially distinguished by how well the surface finish is produced, due to the fact that surface roughness affects several functional attributes of products. Consequently, the desired surface roughness value is usually specified for an individual part, and specific processes are selected in order to achieve the specified finish. Surface specification can also be a good reference point in determining the stability of a production process, because the stability of the machine is contingent on the quality of the operating part.

Being one of the most basic and traditional metal removal processes, single-point turning operations have historically received a great deal of attention in research relating to surface roughness recognition (Dickinson, 1968; Sundaram & Lambert, 1981; Miller et al., 1983). In this research, surface finish in turning operations is influenced in varying amounts by a number of factors, such as feed rate, workpiece material characteristics, workpiece hardness, built up edge (BUE), cutting speed, depth of cut, time of cut, tool nose radius, tool wear, side and end cutting edge angles of the tool, rigidity of the machine tool and workpiece set-up, chatter, and use of coolants, among others. Thus, predicting surface finish during the machining operation is extremely difficult unless some measurement of the product-finish can be obtained from sensor devices.

Before modern surface texture measurement techniques were developed, two tools, one optical and one mechanical, were used to check machined parts. These parts were the eyeball and the fingernail. Human visual acuity in judging the product finish was limited in consistency of judgment by varying light sources as well as part configurations, such as flat surfaces, outside diameters, or curved surfaces, factors which can reflect different amounts of light. Results based on eyesight were often inconsistent, but another test with the fingernail did help to achieve some greater consistency in judging surface finish. The fingernail test relied on the friction produced by the actual surface roughness rather than on geometric features. The sensitivity of the method was limited by the size of the inspector's fingernail in addition to that person's ability to remember and compare tactile sensations from "testing" to "testing". Both methods failed completely as a result of this disadvantage.

One of the major goals researchers in the area of surface roughness prediction techniques have is to develop models able to predict the surface finish of a workpiece under a variety of machining conditions, conditions which are dictated by interrelated, interdependent variations in cutting factors such as feed, speed, tool nose radius, and others. Reliable models would not only make manufacturing process planning and control more simplified, but would additionally contribute to the optimization of the machinability of materials.

In literature reviewed relating to this topic (Jen, 1996; Kim & Klamecki, 1997), current techniques and sensors are not commercially feasible due to their consistently high cost and lack of consistent accuracy. An obvious need has surfaced to develop an effective and inexpensive in-process surface recognition system that would enable implementation of adaptive control in modern manufacturing environments. For this reason, this research seeks to determine the feasibility of using an accelerometer sensor to provide a signal-input of the workpiece condition for a recognition methodology. As the workpiece is being cut, the accelerometer senses the vibration created by the machine motor, insert, and other sources. After collecting the dynamic vibration data from the accelerometer sensor during the turning operations in a lathe machine, an adequate expert system for machining learning and recognition capabilities could be adapted, primarily to reach the goal of inexpensive in-process surface roughness recognition, and secondarily to increase production rates and product quality.

Purpose of this study

Before the surface roughness prediction system can be established in turning operations, the accelerometer must be positioned on the machine where the best signal can be detected. This paper describes a systematic method to identify the location of the sensor for the surface roughness prediction system in turning operations.

Experimental Design

Experimentation was carried out by using the Enterprise Mysore Kihoskar 1550 Lathe (Figure 1). The acceptable feed rate range is between 0.1 ipm (inches per minute) and 20 ipm, and the normal operational spindle speed is 1280 revolutions per minute (rpm) for this machine. The workpiece is a 1018 steel cold rolled finished bar 0.97 inches in diameter and 2.5 inches long, and the tool is a carbide diamond cutting insert. The experimental spindle speed was set at 1280 rpm, a very common setting in industry. Feed rate was considered to be the key surface roughness influence factor according our experience and literature review (Sundaram & Lambert, 1981). The following feed rates were chosen for the experiment (all in inches per minute): 2, 4, 5.8, 7.9, 9.5, 12.4, 14.3, 15.7, 17.3, 19. The surface roughness (Ra) was measured in micro inches (㎡) by a stylus-based profilometer.

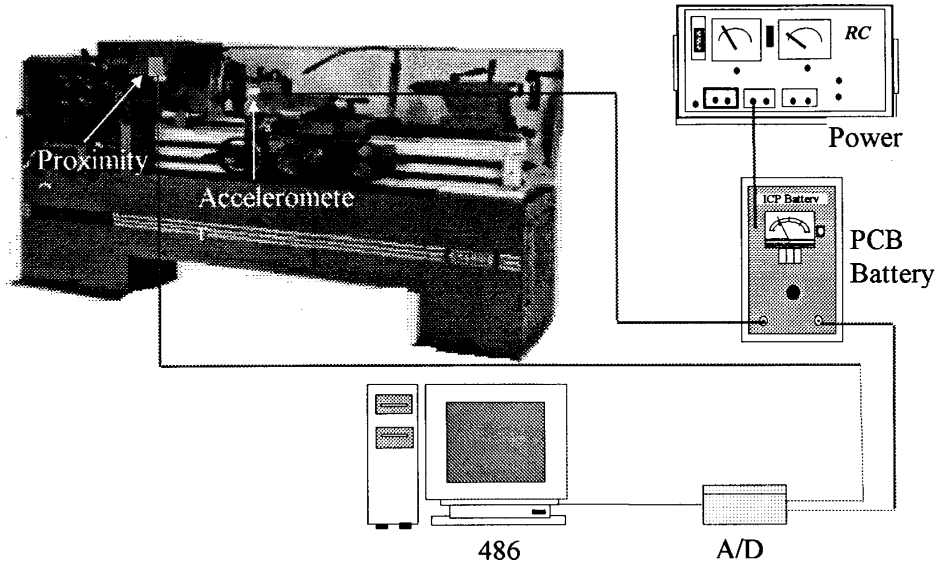

Figure 1. Experimental Setup

The relationship between vibration and surface roughness (R_a) was also studied. As the lathe cuts the workpiece, vibration from the machine influences the surface roughness. The vibration signal can be interpreted as the accumulation of three sub-vibrations in three different directions (X, Y, and Z) as illustrated in Figure 2. The three directional signals can be denoted Vibration X, Vibration Y, and Vibration Z. Which of these is central to influencing the surface roughness of the workpiece is extremely important to on-line surface roughness prediction. In order to determine this, data relating three directional vibrations (Vibration X, Vibration Y, and Vibration Z) were collected under each specified machining condition remarked above.

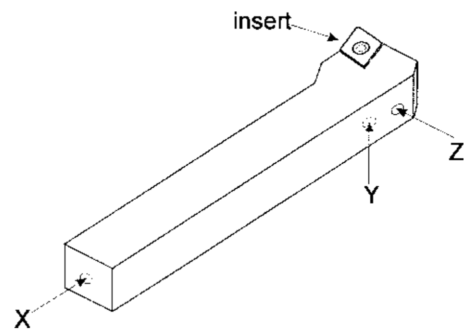

Figure 2. X, Y and Z Direction in Experiment

Experimental Setup

In order to determine which sub vibration signal is the key factor influencing surface roughness, an accelerometer was mounted on the tool holder in X, Y, Z directions separately, so that Vibration X, Vibration Y and Vibration Z could be collected one by one. The X, Y, and Z directions are shown in Figure 2. In order to collect the vibration data resulting from every revolution, a proximity sensor was used to measure the rotations of the spindle. An Omega Das-16000 analog-to-digital (A/D) converter needed to transform analog signals into digital signals was installed to aid in collecting the vibration and revolution data.

In order to collect the data from the experimental design, three different locations have been utilized for experimentation. Each location has 10 different conditional cuts. A total of 5333 data were received from the experimental setup each cut. For example, 10 groups of data were collected for each direction, (X, Y, and Z).

Figure 3 shows an example of the revolution data collected in the X vibration series with a spindle speed of 1280 rpm and a feed rate 2 ipm. The square line represents the revolution data and the erratic line represents the X vibration. The arrow line indicates the range of one revolution. These two sets of data can be combined to obtain the mean of d (d = X, Y, and Z directions) vibration data in each revolution using the following formula:

$$Mean_d\ (i) = \sum_{j=(i-1)*n+101}^{i*n+100} |Vibration(j)| / n,\ d = X \text{ or } Y \text{ or } Z, \quad (1)$$

where i (= 1,2,…,10) represents 10 revolutions, n represents the total number of data in each revolution (in this case n=500), j indicates the vibration data set within the revolution number i. For example, if i = 1, then j represents from 101 to 600.

Using the above formula, the means of X, Y, and Z Vibration of each revolution under a specified feed rate can be calculated and also listed in Tables 1, 2, and 3, respectively.

The vibration means for each cutting condition can be obtained using the following formula:

$$Mean_k = \sum_{i=1}^{10} Mean_d(i) / 10, k = 1, \cdots, 10,$$

where k indicates the cutting conditions, d indicates the vibration direction of X, or Y or Z.

Results And Discussion

Each vibration data set was collected in a period of more than ten spindle revolutions. Since a proximity sensor was collecting revolution data simultaneously, the vibration data could be identified and thus separated into revolutions. Ten vibration data sets per revolution for each separate feed rate were randomly selected and calibrated by setting their algebra sum to zero. These data sets were taken as absolute values after calibration. The mean value of each data set was then computed. The ten mean values from the same feed rate were calculated for a grand mean and deviation. This grand mean was the Vibration Amplitude Average (VAA) for that feed rate. The surface roughness was measured as a Roughness Average (Ra) with the Surface Roughness Gage as soon as a cutting was finished. Three measurements were taken for each feed rate, and the mean and the standard deviation were then computed.

The relationship between the VAA and fed rate in the three sensor locations was shown in Figure 4. A linear regression analysis was conducted for each data-pairs and was shown in the Figure 4 as well. The square of the linear regression coefficients (R^2) are 0.0001, 0.813 and 0.2282 for X, Y and Z locations, respectively. The relationship between Ra and VAA was plotted in Figure 5. Both the linear correlation coefficient (R^2) and the Pearson product moment correlation coefficient (r) analyses were conducted. The R^2 values are 0.0562, 0.6369 and 0.0653 for X, Y and Z locations, respectively, as shown in each plot. The Pearson product moment correlation coefficient was calculated using Equation 2. The r values for X, Y and Z locations were 0.2134, 0.7180 and 0.2299, respectively.

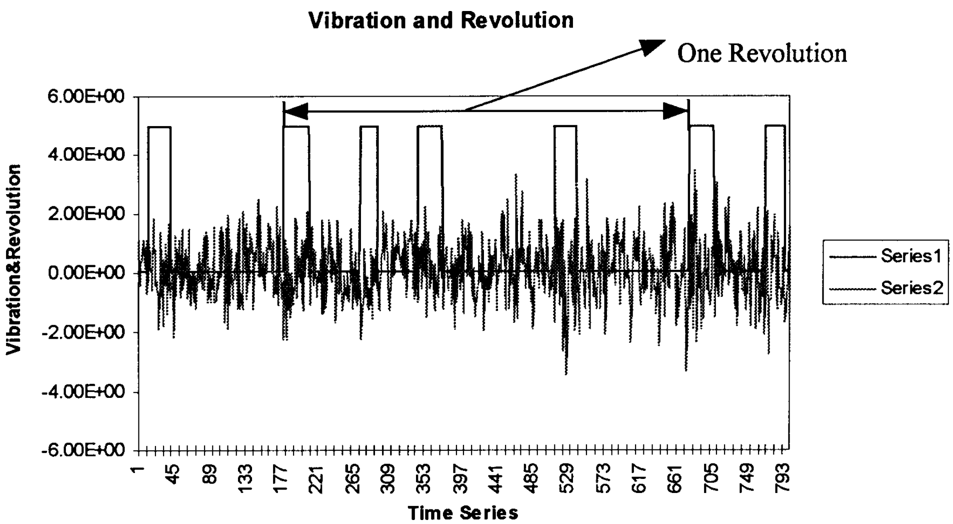

Figure 3. Original X Vibration under feed rate 2 ipm

Revolution	Feed Rate (in/min)									
	2	4	5.8	7.9	9.5	12.4	14.3	15.7	17.3	19
1	0.0206	0.0195	0.0196	0.0189	0.0174	0.0141	0.0191	0.0182	0.0170	0.0228
2	0.0210	0.0199	0.0198	0.0196	0.0197	0.0312	0.0198	0.0174	0.0172	0.0201
3	0.0186	0.0188	0.0182	0.0205	0.0199	0.0161	0.0219	0.0156	0.0172	0.0205
4	0.0199	0.0190	0.0197	0.0196	0.0213	0.0158	0.0207	0.0182	0.0173	0.0222
5	0.0187	0.0199	0.0189	0.0193	0.0194	0.0145	0.0206	0.0183	0.0148	0.0235
6	0.0191	0.0191	0.0198	0.0202	0.0169	0.0143	0.0217	0.0184	0.0177	0.0234
7	0.0182	0.0199	0.0192	0.0252	0.0183	0.0165	0.0200	0.0178	0.0211	0.0208
8	0.0184	0.0190	0.0199	0.0230	0.0200	0.0163	0.0214	0.0162	0.0192	0.0231
9	0.0184	0.0202	0.0180	0.0215	0.0221	0.0155	0.0190	0.0177	0.0165	0.0202
10	0.0179	0.0178	0.0219	0.0216	0.0226	0.0160	0.0229	0.0186	0.0159	0.0243

* Data are in mv, which are the vibration signals from the accelerometer.

Table 1. Vibration data for X location

$$\rho_{VR} = \frac{\sum (V_i - \bar{V})(R_i - \bar{R})}{N \sigma_V \sigma_R} \quad (2)$$

V - vibration amplitude average (VAA); $\bar{V}$ is the grand mean of VAA
R - roughness average (Ra); $\bar{R}$ is the grand mean of Ra.
s - standard deviation
N - number of data sets

According to the above results, The Y location is obviously the best in respect to obtaining vibration information to detect the surface roughness of the work piece. At the Y location, not only did Ra have the highest R^2 and r values against VAA, but the VAA also had the highest R^2 values against feed rate. At the X and Z locations, all the R^2 and r values were low. In regard to the VAA, both Y and Z locations had similar greater values (Figure 4). However, the VAA data from the Y location possesses greater correlation to both feed rate and Ra (higher R^2 and r values). Interestingly enough, the Y location did not receive the strongest vibration signal, though it collected the most corresponding information to the surface roughness of the work material. This implies that the strongest vibration signal is not necessarily the most useful for determining surface roughness.

The major cutting force impacts at the Y direction as shown in Figure 2. The total cutting force of a turning operation accounts for about 99% of the power required by the process, while the feed force (at the Z location) accounts for only about half of the cutting force (DeGarmo et al., 1997). Even though the force at the Z location is less than that at the Y location, it causes a stronger vibration (Figure 4). This is probably due to the effect of the difference of the tool orientation at the two different locations. Because of the way this experimental setup is designed, the tool must cut into the material in the Y direction at a sharp angle. Chips can then be easily formed in the Y direction so that resistance to the cutting force is reduced. The feed force feeds the tool in the Z direction to make a continuous cutting possible. No chip is formed in the Z direction. The tool is just forced to insert into the work piece to make room for a new cut. The resistance to the feed force is thus strong. This, in turn, causes the strongest vibration.

In a milling operation, Kim & Klamecki (1997) found that the change of rotation frequency of the spindle is a reliable source to predict the machining performance. In turning operations, the spindle is the work piece and the change of the rotation frequency generates direct vibration in the cutting direction, or the Y direction. This study, therefore, confirms what Kim and Klamecki found in their study. It is further confirmed that the change of cutting force carries information associated with the finished surface roughness. Thus, the vibration caused by this force is closely associated with the finished surface roughness. The square of the correlation coefficient value in this study ($r_{VR}^2 = 0.5155$), indicates that the proportion of variance in surface roughness is associated with variance in vibration amplitude. Or, in other words, 51.55% of the vibration signal is associated with surface roughness.

Conclusion

The Y location, even though it does not receive the strongest vibration signal, is the prime location for detecting surface roughness information from the vibration signal regardless. The cutting force is very likely the carrier

Revolution	Feed Rate (in/min)									
	2	4	5.8	7.9	9.5	12.4	14.3	15.7	17.3	19
1	0.0265	0.0276	0.0265	0.0352	0.0309	0.0428	0.0355	0.0389	0.0269	0.0392
2	0.0261	0.0282	0.0295	0.0330	0.0336	0.0342	0.0350	0.0335	0.0295	0.0412
3	0.0238	0.0305	0.0338	0.0344	0.0352	0.0315	0.0340	0.0341	0.0327	0.0478
4	0.0254	0.0293	0.0507	0.0301	0.0292	0.0330	0.0370	0.0362	0.0349	0.0448
5	0.0260	0.0283	0.0298	0.0328	0.0354	0.0437	0.0460	0.0355	0.0342	0.0439
6	0.0253	0.0318	0.0287	0.0334	0.0340	0.0306	0.0337	0.0372	0.0340	0.0408
7	0.0232	0.0371	0.0319	0.0319	0.0334	0.0356	0.0359	0.0388	0.0650	0.0527
8	0.0230	0.0261	0.0303	0.0394	0.0317	0.0335	0.0341	0.0362	0.0374	0.0452
9	0.0243	0.0302	0.0306	0.0303	0.0319	0.0347	0.0336	0.0381	0.0304	0.0462
10	0.0259	0.0287	0.0322	0.0359	0.0321	0.0296	0.0579	0.0391	0.0301	0.0387

* Data are in mv, which are the vibration signals from the accelerometer.

Table 2. Vibration data for Y location

Revolution	Feed Rate (in/min)									
	2	4	5.8	7.9	9.5	12.4	14.3	15.7	17.3	19
1	0.0378	0.0320	0.0421	0.0432	0.0305	0.0483	0.0481	0.0495	0.0391	0.0409
2	0.0352	0.0353	0.0361	0.0433	0.0298	0.0490	0.0493	0.0525	0.0432	0.0398
3	0.0325	0.0337	0.0360	0.0420	0.0285	0.0473	0.0505	0.0523	0.0369	0.0435
4	0.0341	0.0338	0.0392	0.0425	0.0296	0.0519	0.0476	0.0524	0.0410	0.0378
5	0.0350	0.0351	0.0351	0.0414	0.0303	0.0522	0.0452	0.0524	0.0372	0.0408
6	0.0364	0.0323	0.0324	0.0442	0.0332	0.0480	0.0481	0.0481	0.0434	0.0391
7	0.0345	0.0339	0.0352	0.0422	0.0297	0.0511	0.0453	0.0477	0.0414	0.0468
8	0.0365	0.0352	0.0384	0.0414	0.0325	0.0469	0.0515	0.0466	0.0402	0.0400
9	0.0313	0.1158	0.0428	0.0408	0.0299	0.0454	0.0509	0.0509	0.0460	0.0416
10	0.0322	0.0364	0.0401	0.0394	0.0318	0.0482	0.0463	0.0525	0.0383	0.0430

* Data are in mv, which are the vibration signals from the accelerometer.

Table 3. Vibration data for Z location

of the valid signal for detecting surface roughness of finished products. Therefore, the Y location should be used to detect vibration signals in further study of machining performance, in particular for the roughness prediction systems.

With this experiment and statistical results, the authors found Y location the right location for the sensor to be set up at in order collect data for developing the on-line surface roughness recognition system in turning operation. By enlarging the number of factors incorporating with some expert systems (such as fuzzy logic, neural networks), the on-line roughness recognition system could be developed and implemented in the industry. The authors also believe that this study can be used for industrial technology curriculum to help graduates understand the nature of surface roughness inspection technique, turning operation nature, and the statistical tools for research.

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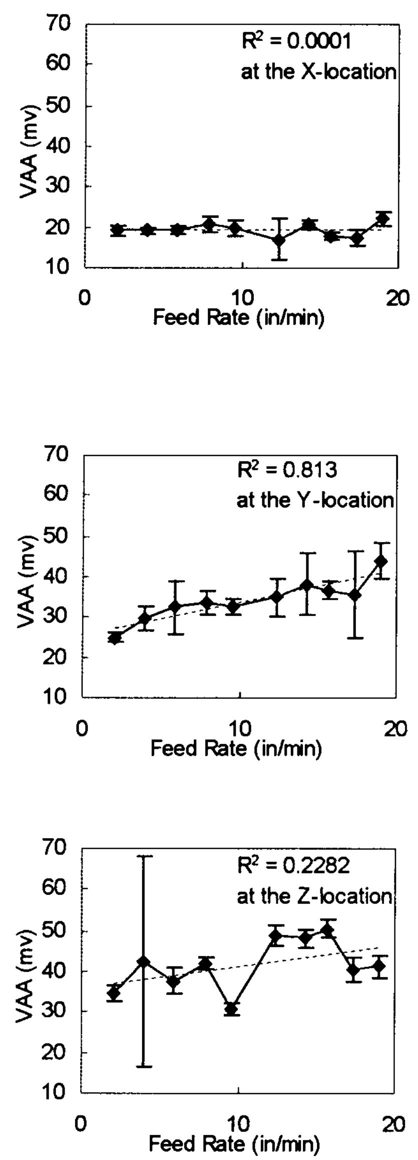

Figure 4. The relationship between the vibration amplitude average (VAA) and the feed rates at different sensor locations.

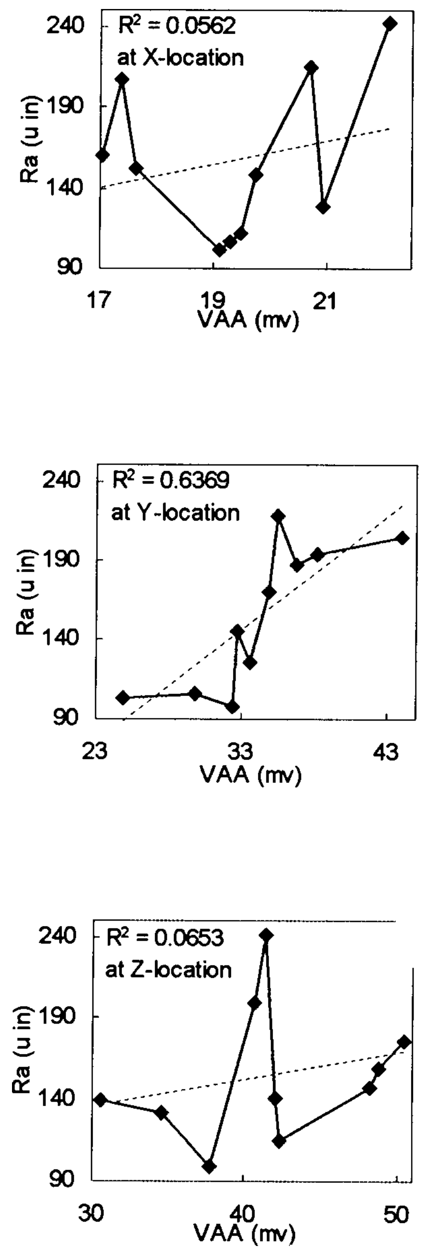

Figure 5. The relationship between the surface roughness (Ra) and the vibration amplitude average (VAA) at different locations.